MODELLING THE EFFECT OF WEATHER ON TOURISM: DOES IT VARY ACROSS SEASONS?

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Abstract

Weather conditions are important determinants of tourism demand. After reviewing the main contributions of previous research about the role of climatic variables in tourism demand functions, we explore different modelling alternatives to introduce temperature and rainfall in a gravity model. The dataset used comprises interregional tourism flows by Spanish residents from 2011 to 2015. We first estimate a benchmark model with both temperature and rainfall at the destination expressed in levels, and then consider some extensions to this model. In particular, special attention is paid to analyzing whether the sensitivity that tourists may have to weather factors can change across seasons. Other modelling issues examined in this study include the relationship between climatic variables at the destination and at home, the influence of weather in previous periods (lagged values of temperature and rain), the variability of the weather variables (captured by the standard deviation of these variables), or whether the effect of temperature varies with the climatic characteristics of the region. Our empirical results confirm that spring and summer tourism in Spain is more sensitive to weather conditions, that the number of domestic overnight stays in Spain is strongly influenced by changes in the difference in temperature between tourists' home and destination regions, that the estimated parameters of lagged weather variables are higher than those corresponding to the travelling months, that temperature variability in the destination region reduces tourism demand, and that the effect of temperature on destination choice for residents in moderate-climate regions is lower than for residents in other types of regions.

JEL classification: L83, R12, C23, Q54

Keywords: Domestic tourism flows, gravity model, weather, Spanish regions, seasons, climatic variables.

1. Introduction

Tourism is one of the most climate-sensitive economic sectors. Climatic variability and weather events alter individuals' decisions about where they travel, how long they stay, and how frequently they choose to visit a destination (Bujosa & Roselló, 2013, Craig &

Feng 2018). In some papers, the terms climate and weather are often used interchangeably, and although the two are related, long-term climate patterns are established by entirely different factors than those regarded as short-term weather (Cooke, 2012). Specifically, in Wilkins et al. (2018), weather is defined as the "*atmospheric condition at any given time or place*," whereas climate is "*the average weather across a period of over 30 years*" (United States Environmental Protection Agency, 2013). While climate and weather are both important for destination selection, weather is also influential during the trip, altering activities, travel plans, and the length of the stay.

For these reasons, the tourism industry is becoming increasingly interested in learning about the effect of weather on tourist flows to better design promotional campaigns to attract visitors. If the influence of weather as a pull factor changes across seasons, tourist products and commercial strategies should be adapted accordingly. Additionally, since climate change is creating new challenges, it is also important for policymakers to study the effect of the average weather conditions and weather variability on tourist flows over a span of time (Becken, 2013 a, Fang et al., 2018).

Data on atmospheric conditions such as temperature and rainfall on a daily, monthly or annual scale are recorded, archived and analysed in meteorological observatories and serve as the basis for short-term weather forecasts and the statistical study of long-term climate trends. In the field of tourism, the effects of weather have been investigated through various approaches. First, tourism demand is modelled with the inclusion of weather determinants (Goh, 2012). Second, the attractiveness of tourist destinations is measured by using climate indexes (Pröbstl-Haider et al*.,* 2015). Furthermore, to assess climate change and its potential impacts on tourist flows, it is necessary to study the long-term weather patterns over a specific time frame in a specific area (Dube & Nhamo, 2019; Liu, 2016).

Our study explores how weather conditions (monthly averages of temperature and rainfall) affect tourist demand. More specifically, we consider temperature and rainfall as explanatory factors for monthly domestic tourism inflows. While most tourism demand studies analyse the effect of weather conditions on tourism in a single season or using annual data, very few papers have compared model findings between different seasons (Krstinic & Sverko, 2018; Hestetune et al., 2018). The purpose of this research is to determine whether variations in temperature and precipitation affect tourist demand differently across seasons.

There are different ways to model the effect of climate elements on tourist demand (Rosselló, 2014). We use a gravity model, which has become a common tool to explain tourist flows between territories, at the country (Santana et al., 2016), region (Cafiso et al., 2018) and city (Zhang & Zhang, 2016) levels. We estimate different models to study the role of weather considerations in Spanish residents' choice of travel destination. We use monthly panel data of interregional tourist flows observed for five years (2011-2015).

2. Modelling the effect of weather

For many years, the literature has omitted climate elements from tourism demand models (Crouch, 1994). Studies have focused on estimating income and/or price elasticities as the main determinants of tourist demand. One of the first attempts to study the impact of weather conditions on tourists' choice of destination was the paper by Barry & O'Hagan (1972). They modelled the decision of UK tourists to choose Ireland as a destination and considered weather at the destination as an explanatory variable.

In this section, we review the main approaches employed to study the effect of weather on tourist demand. There are many different types of studies that vary depending on the type of data (individual vs aggregate), the structure of the data (panel, time series, or cross-section), the type of tourist (domestic vs international), the geographical unit (city, region or country), etc. Given the large heterogeneity existing in the literature, we review previous papers in several groups:

a) Different weather variables

While the most common variable is temperature, other variables have been considered. For example, Zhang & Kulendran (2016) considered humidity, visibility and thunderstorms when modelling Hong Kong's inbound tourism demand from mainland China, Taiwan, South Korea and Japan. Wind speed at the destination has also been included in several papers, such as Ridderstaat et al. (2014). In addition, Taylor & Ortiz (2009) and Agnew & Palutikof (2006) used the number of sunshine hours as a variable. Other papers have also found that climate variability is a significant push factor for tourist demand. Saverimuttu & Varua (2014) showed that there is a significant increase in US tourist arrivals in the Philippines when the Southern Oscillation Index, a measure of climate variability, reflects a cold phase in the home climate.

Tourists take into consideration the combined effect of these variables, and therefore, the effect of weather should not be addressed by modelling each variable separately. Thus, the relationship between weather and tourism has also been studied using climatic indexes. For example, Barry and O'Hagan (1972) used a Poulter weather index that considers temperature, rainfall and hours of sunshine in the summer months.

In fact, several papers (e.g., Amelung et al. (2007); Moore (2010) and Goh (2012)) have used the Tourist Climatic Index developed by Mieczkowski (1985), which is a weighted average of seven climatic variables: monthly means for maximum daily temperature, mean daily temperature, minimum daily relative humidity, mean daily relative humidity, total precipitation, total hours of sunshine and average wind speed.

Use of other weather indexes has been proposed in the literature. De Freitas (2003) suggested that tourism is influenced by a few weather conditions, including aesthetic factors (e.g., sunshine, solar radiation, high visibility, and cloud cover) and physical factors (wind and rain). Eugenio-Martin & Campos-Soria (2010) developed a tourism climate index that measures the number of months with "good weather". The index is built by summing a set of monthly dummy variables that represent levels, such as when the average temperature or number of days per month with rainfall is between a particular range.

b) Different ways to measure weather variables

Most papers have used average values for time periods. That is, if the data are monthly, a climatic variable such as temperature is usually measured as the average temperature in the month. However, climatic variables can be measured in other ways. For example, Lise & Tol (2002) employed variables measured at the most representative period for travelling (average day and night temperatures of the warmest month), while for rainfall, they considered cumulative precipitation instead of average precipitation. Other papers have analysed the extreme values of the dataset. Maddison (2001) used average maximum daytime temperature and precipitation on quarterly data. Nunes et al. (2013) used the mean of maximum daily temperatures during the summer.

c) Difference between weather conditions at the destination and origin

The majority of papers have only considered weather at the destination, but weather conditions in the region of origin can also influence the demand for tourism. Eugenio-Martín & Campos-Soria (2010) tested the hypothesis that the climate in the region of residence is a determinant of holiday destination choice. Their results showed that residents in countries with more comfortable climates are more likely to have more domestic travel than international travel.

Some papers have tried to reflect the climatic difference between origin and destination. Zhang & Kulendran (2016) included the relative temperature in their model (Hong Kong's temperature divided by the temperature of the tourist's home country). Li et al. (2017) used the difference between climatic factors (maximum temperature, minimum temperature, average temperature, average humidity, average precipitation, and average hours of sunshine) measured at the origin and destination. Li et al. (2018) proposed a relative climate index that measures the climatic comfort of a destination relative to that of the tourist's origin. Turrión-Prats & Duro (2019) found that international tourism demand is highly dependent on temperature differences between tourists' home and destination countries.

In addition, Grigorieva (2019) demonstrated the utility of the Acclimatization Thermal Strain Index for Tourism in decision-making processes. This index quantifies the physiological expenses that tourists incur during the acclimatization process when travelling due to the climatic differences between the destination and their place of origin.

d) Different modelling

As stated before, most papers will consider a single variable, mainly temperature, and introduce it in the model in levels (with or without logs). However, the effect of climatic variables seems to be more complex.

For example, some papers have allowed for nonlinear effects by considering short polynomial forms. Bigano et al. (2006) introduced temperature squared, which examines optimal temperatures to travel, to analyse the holiday destination choice of tourists from 45 countries. Lise & Tol (2002), using cross-sectional data of tourist arrivals and departures in eight countries, included both the warmest temperature and its squared value to find the optimal summer temperature for tourism. Maddison (2001) included the average maximum daytime temperature as linear, quadratic, cubic and quartic terms to explore optimal temperatures at the destination.

The effect of changes in weather over time may not be contemporaneous. Since some trips are scheduled in advance, it may be possible that the relevant weather for a tourist decision is not the weather at the period of travel but at a previous time. In this sense, Kulendran & Dwyer (2012) measured the impact of current and lagged values of maximum temperature and hours of sunshine on seasonal variation in Australian inbound holiday tourism.

As suggested by Butler (2001), Amelung et al. (2007) and Hadwen et al. (2011), the two main causes of seasonality in tourism can be divided into natural and institutional factors. The former is related to climate conditions, such as temperature and precipitation, while the latter is driven by traditional social activities and social rules, including religious and major holiday periods.

Within this context, one group of researchers estimated the influence of climatic variables on seasonal variations in tourism demand (Hadwen et al. 2011; Kulendran & Dwyer, 2012; Ridderstaat et al. 2014; Fang & Yin, 2015; Chen et al. 2017; Nakahira & Yabuta, 2019).

Furthermore, the effects of climate variability can be separated into intra-annual seasonality and interannual variability. Intra-annual seasonality is the effect of short-term weather variation from quarter to quarter. For example, a hotel or destination may experience different levels of visitation over the different quarters of the year, with the greatest difference between visitation in the summer and winter. To assess the influence of the climate's intra-annual variability, the estimations of tourism demand models include all months of the year within the same regression equation instead of estimating a different model for each month (Bigano et al., 2005; Amelung & Moreno, 2012). In this way, if seasonality is regarded as deterministic, introducing monthly dummy variables in the models is sufficient to account for the seasonal fluctuations (Song & Li, 2008; Athanasopoulos & Hyndman, 2008).

On the other hand, climate variation can affect tourist flows within any given season. For example, a particularly cold or rainy winter (often referred to as unseasonal conditions) as compared to average years in the destination might contribute to increased or decreased tourist arrival. Nevertheless, Becken (2013 b) and Li et al. (2018) suggested that tourism demand is unlikely to be affected by the deviation of climate from its long-term average. Both studies concluded that tourists' travel decisions are mainly determined by the relative intra-annual seasonality.

However, we believe that it is necessary to consider that the effects of weather variation on tourism may vary across seasons. That is, an increase in temperature could have a different effect on tourist demand in the summer than it has in the winter. We are therefore proposing to include an interaction between seasonal dummies and temperature to test whether the effect of temperature on tourist flows differs across the seasons. The attention devoted by the tourism literature to the interaction effects between climatic variables and seasons has been quite limited. Wilkins et al. (2018)

included the interaction of location and season to evaluate whether the effect of seasonality varies across locations. In addition, the question of whether the effect of weather on tourism demand varies across regions of origin has been largely overlooked in the literature. Nunes et al. (2013), constituting the only exception, showed that increases in maximum temperature during the summer in Tuscany led to a sizable decline in the number of domestic tourists, while temperature was insignificant for international tourists.

Recent studies (Falk, 2014 or Wlikins et al., 2017) have analysed the impact of climate factors on tourism demand by estimating separate models for different seasons. However, we believe that our proposal fills a gap in this literature because our study allows for the effect of temperature on domestic tourism to be different across seasons and regions of origin. To do this, we interact the log of climatic variables with seasonal and regional dummies in the context of a gravity model.

3. Empirical Model

There are different approaches to modelling tourism demand (Rossello, 2014). We use a gravity model to evaluate the effects of climatic variables on bilateral tourist flows. The gravity model has been extensively used for the analysis of bilateral trade flows (Tinbergen, 1962; Anderson, 1979). In the field of tourism, gravity equations have been used to estimate the determinants of tourism flows (Eilat & Einav, 2004; Khadaroo & Seetanah, 2010; De la Mata & Llano, 2012; Massida & Etzo, 2012; Marrocu & Paci 2013; Morley et al., 2014; Rossello & Santana, 2014). A gravity model in tourism can be written as:

$$N_{ijt} = f\ (ZO_{it}, ZOD_{ijt}, ZD_{jt}) \tag{1}$$

where N_{ijt} denotes the number of visitors or overnight stays from origin region *i* to destination region *j* at period *t;* ZO_{it} is a vector of variables that reflect the push factors for outbound tourists from region *i* (GDP per capita, population); ZOD_{ijt} represents the travel costs from *i* to *j,* including the distance; and ZD_{jt} is a set of variables relating to the pull factors for inbound tourists to region *j* (surface area, coast, etc.).

We augment the gravity equation with different specifications of climatic variables and some control variables, such as time effects. The empirical model to be estimated, in a log-linear form, is the following:

$$LnNIGHTS_{ijt} = \beta_0 + \beta_1 LnGDPpc_{it} + \beta_2 LnPOPULATION_{it} + \beta_3 DISTANCE_{ij} + \beta_4 LnAREA_j + \beta_5 PARKS_{jt} + \beta_6 D\_CITY_j + \beta_7 D\_COAST_j + \beta_8 D\_EASTER_t + \beta_9 D\_MADRID_j + \beta_n LnCLIMATIC\ VARIABLES_{ijt} + \gamma_t + \delta_t + u_{ijt} \qquad (2)$$

where *Ln* represents natural logs; β_0 …, β_9 are the parameters to be estimated for the baseline gravity model; β_n is the vector of parameters of the different climatic variables; γ_t and δ_t are monthly and yearly time effects, respectively; and u_{ijt} is a disturbance term. The main reason to specify our model in log-log form (that is, taking natural logs of both the dependent and the continuous independent variables) is to give flexibility to the specification. In a double-log functional form, the marginal effects depend on the levels of both the dependent and the independent variables.

We use the number of nights spent at the destination (overnights) as the dependent variable. With regard to our independent variables, we first consider the push factors that determine the potential for outflow of tourists from the region of origin. Personal income was taken into consideration by including the regional gross domestic product per capita ($\boldsymbol{GDPpc_{it}}$). The population in the region of origin ($\boldsymbol{POPULATION_{it}}$) was also included to control for the size of the region of origin.

The next set of variables attempt to account for relevant characteristics of the region of destination that are considered to act as pull factors. We consider the surface area (in km^2) of the region ($\boldsymbol{AREA_j}$) as a control factor. Other pull factors include the number of national parks ($\boldsymbol{PARKS_{jt}}$) and whether it is a coastal region ($\boldsymbol{D\_COAST_j}$ takes the value one when the destination has a coastline). Since some cities are visited for their cultural heritage even if they are not on the coast, we include the dummy variable $\boldsymbol{D\_CITY_j}$, which takes the value one when the region of destination has special features that attract tourists, such as well-known museums or historical sites. Additionally, we include a dummy variable to control for Madrid as a destination region ($\boldsymbol{D\_MADRID_j}$) since it has been argued that the capital of the country (or the main city) exhibits tourist behaviour that is different from that in the rest of the regions.

Finally, to examine the influence of institutional factors on seasonal tourism demand, in addition to monthly and annual effects, we include a dummy variable to capture the impact of Easter ($\boldsymbol{D\_EASTER_t}$) since a large number of people use this holiday period to travel. The fact that the Holy Week calendar causes Easter to fall in March or April, depending on the year, explains why it should be modelled separately, unlike Christmas, which always falls in December.

Our specification also contains the geographical distance between the capitals of the regions as a proxy for transportation costs ($\boldsymbol{DISTANCE}_{ij}$). We are aware that the use of travel times or transportation costs by mode would be more accurate, but there were no appropriate data.

As we have mentioned in Section 2, to analyse the natural factors of seasonal patterns of domestic overnights in Spain, we estimated a gravity model including temperature and rainfall as additional explanatory variables, referring to both the tourists' destination and home regions.

Regarding the variables of interest, we propose different ways to model the effect of weather as a determinant of domestic tourism flows in Spain. We compare some of those alternatives and propose some new specifications to estimate equation (2). The different specifications of climatic variables are as follows:

a) Standard modelling of the weather at the destination (Model 1)
   - $TEMP\_D_{jt}$: Average monthly temperature in the capital of destination region *j* during month *t* (in degrees Celsius).
   - $RAIN\_D_{jt}$: Total monthly rainfall in the capital of destination region *j* during month *t* (mm).
b) Dispersion of temperatures (Model 2)

Tourists dislike unexpected weather changes. We measure weather variability through the standard deviation of temperature in region *j* during each year.

   - $SD\_TEMP\_D_{jt}$**:** Standard deviation for the temperature of region *j* during year *t*.

c) The climatic variables at both the destination and origin

We consider three different specifications:

- $TEMP\_D_{jt}$, $TEMP\_O_{it}$, $RAIN\_D_{jt}$ and $RAIN\_O_{it}$ as separate variables. This is the most general specification, although it assumes that the effect of both temperatures (rainfall) is independent of the other (Model 3).
- Lagged variables (Model 4). Since some tourist trips are planned ahead, tourists may take into account the prevailing weather at the time they made the decision to travel instead of the weather at the time of travelling. $TEMP\_D_{jt-1}$ is the average monthly temperature in the region´s capital of destination *j* during the

previous month to the month of travel. In addition, we include lagged variables of $TEMP\_O_{it-1}$, $RAIN\_D_{jt-1}$, $RAIN\_O_{it-1}$.

– The ratio of the temperatures of the destination and origin. In this way, the effect of the temperature at the destination depends on the temperature at the origin (Model 5).
    - $TEMP\_R_{ijt}$: Relative temperature (monthly average temperature at the destination divided by the temperature at the origin). The effect of a one-degree increase in the destination temperature ($\beta_n / TEMP\_O_{it}$) decreases with the level of temperature at the origin, which seems to be a sensible specification.
    - $RAIN\_R_{ijt}$: Relative rainfall (rainfall at the destination divided by rainfall at the origin).

d) The effect of temperature varies with the seasons (Models 6 and 7)

We expect the effect of weather variation not to be equal throughout the year. That is, a one-degree increase is not likely to have the same effect in summer as it has in winter. For this reason, we allow the effect of temperature to be different across seasons by interacting the log of average temperature with a seasonal dummy, autumn (October, November and December) being the excluded category (Model 6).

The aim of model 7 was to test whether the effect of relative temperature varied with season.

e) The effect of temperature varies with the type of origin region (Model 8)

The effect of, for example, an increase in temperature, is likely to be different for residents in cold regions than it is for residents in warm regions. For this reason, we interact the log of average temperature at the destination with regional dummies. We form three groups of regions depending on their type of climate. One group included continental regions (Aragon, Castilla-La Mancha, Castile and León, Extremadura, La Rioja, Madrid and Navarre); the second group included Mediterranean regions (Andalusia, Balearic Islands, Catalonia, Valencia Community and Murcia) and the Canary Islands; and the third group, which was the excluded category, included northern regions (Asturias, Cantabria, Galicia and Basque Country).

4. Data Source and Descriptive Statistics

We use aggregate data for monthly flows of domestic tourists between each pair of 17 Spanish regions during the period of 2011-2015. We excluded trips within the same node (origin/destination). This implies that we did not consider intraregional flows. The inter-regional flows represent approximately 70% of the total domestic flows in Spain. In 2015, these flows reached 31 million total arrivals of resident tourists and 75 million overnights.

Although the flows can be measured in daily visitors or in overnight visitors, we present only the results for overnight stays. The original data were at the provincial level (NUTS III), but we aggregated the data at the regional level (NUTS II). Therefore, we have a balanced panel of 272 flows (17*16), observed monthly over five years, for a total of 16,320 observations. Table 1 contains the definition of the main variables used in the empirical models.

Table 1. Description of variables used in the empirical analysis

VARIABLE	DEFINITION	DESCRIPTION	SOURCE
$NIGHTS_{ijt}$	Overnights in region *j* from region *i* in month *t*	Dependent variable	Spanish Hotel Occupation Survey (2011-2015)
$GDPpc_{it}$	Annual per capita Gross Domestic Product at constant prices (Base 2010) in region *i*	Push factor	Spanish Statistical Office (2011-2015)
$POPULATION_{it}$	Annual population in region *i*	Push factor	Spanish Statistical Office (2011-2015)
$DISTANCE_{ij}$	Distance between the regions' capitals (Km)	Proxy of transportation costs	Google maps (2019)
$AREA_j$	Size of the region of destination (Km^2)	Pull factor	Spanish Statistical Office (2019)
$PARKS_j$	Number of national Parks in region of destination	Pull factor	Spanish Statistical Office (2011-2015)
D_CITY_j	Region of destination with one of five most visited cities by resident's tourists, except for Madrid.	Pull factor	Tourist Movements of Spaniards Statistics (FAMILITUR) (2011-2015)
$TEMP\_O_{it}$	Average monthly home temperature of Region´s capitals *i* during month *t* (º C)	Push factor	Spanish Statistical Office (2011-2015)
$TEMP\_D_{jt}$	Average monthly temperature in the capital of destination region *j* during month *t* (º C)	Pull factor	
$RAIN\_O_{it}$	Monthly total rainfall in the capital of origin region *i* during month *t* (mm)	Push factor	

$RAIN\_D_{jt}$	Monthly total rainfall in the capital of destination region j during month t (mm)	Pull factor	

The tourist flows were obtained from the Hotel Occupancy Survey. An interesting feature of this data source is that it does not include trips made by Spanish residents to the homes of family or friends, which represent approximately 63% of total overnight visits. Since it is very likely that in these kinds of trips, the role of weather may less influence the destination choice (Scott et al., 2012), we preferred not to consider them.

Table 2 shows the descriptive statistics for the variables used in the empirical analysis.

Table 2. Descriptive Statistics of variables used in the empirical analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
$NIGHTS_{ijt}$	16,320	22,295.64	45,320.73	25	884,895
$GDPpc_{it}$	16,320	22,192.61	4,443.425	15,274	31,807
$POPULATION_{it}$	16,320	2,753,724	2,455,370	317,053	8,449,985
$DISTANCE_{ij}$	16,320	686.75	504.92	71	2,243
$PARKS_{jt}$	16,320	6.06	5.07	0	15
$AREA_{j}$	16,320	29,755.88	29,570.27	5,000	94,200
$TEMP\_D_{jt}$	16,320	16.34	6.34	2.8	30.6
$RAIN\_D_{jt}$	16,320	47.59	54.18	0.1	409.1
$SD\_TEMP\_D_{jt}$	16,320	5.62	1.23	2.56	7.69

Source: Own elaboration.

5. Estimation and Results

All models were estimated by ordinary least squares (OLS). The results are shown in Table 3. The estimated coefficients for the continuous variables (all expressed in logs) can be interpreted as elasticities. Elasticities measure the percent change in the dependent variable when one independent variable increases by one percent (holding the rest of the explanatory variables constant). For example, the first estimated coefficient in Table 3 indicates that if GDP per capita in the region of origin increases by one percent, the number of overnight stays will increase by 1.15%. Almost all the estimated coefficients are highly significant. The value of R^2 ranges between 78.1% and 79.2%. All statistical analyses were performed using the statistical software Stata 15.

5.1. Non-climatic variables

In general, the estimates were very robust since they do not change sign and the size is very similar across the different models. A positive elasticity, very close to one, is estimated for per capita GDP. This result is similar to that found by Marrocu & Paci (2013) for Italian domestic tourism flows, and it is close to the value of 0.86 obtained by Garín (2009) for the region of Galicia (northwestern Spain) and in line with the range of values reported by Alvarez-Diaz et al. (2020) for the Spanish provinces. However, these elasticities are lower than those estimated by Massida & Etzo (2012) and Guardia et al. (2014), where the demand for domestic tourism was classified as a luxury good.

Additionally, we found an elasticity of population that is just below one, which was slightly higher than the elasticity found in some previous studies (e.g., 0.75 in Priego et al., 2015 and 0.85 in Guardia et al., 2014), but similar to the value of 0.97 obtained by Alvarez-Diaz et al. (2020) in their gravity model.

Regarding the distance between the origin and destination, we found that it exerted a negative impact on domestic tourism demand as, for example, Cafiso et al. (2018) highlight. The average distance elasticity estimated (-0.54) was smaller, in absolute value, than the averages shown in the literature relating to Spanish tourism demand (e.g., -0.90 in Priego et al., 2015). This difference can be explained because in the present study, we excluded intraregional tourism flows, unlike in the works by De la Mata & Llano (2012) and Guardia et al. (2014). We believe that by not taking into consideration the choice of spending holidays in the region of origin, the effect of distance on overnight stays at tourist establishments was moderated.

The pull factors used to assess destination attractiveness have different intensities. With a positive elasticity (0.344), $\boldsymbol{AREA_j}$ controls the size of each destination region. National parks are also an important pull factor, in accordance with the results of Marrocu & Paci (2013) and Alvarez-Diaz et al. (2020). Furthermore, the positive and significant sign for D_CITY_j confirms that many regions are visited because they have a city with historical and cultural heritage (Patuelli et al., 2013) and, similarly to other studies (De la Mata & Llano, 2012 and Priego et al., 2015), the high coefficient of the dummy variable to control for *Madrid* as the destination implies that the capital of the country displays a tourist behaviour that is different from that of the rest of the regions. In addition, the dummy $\boldsymbol{D\_COAST_j}$ shows that if all other factors remain the same, coastal regions receive more domestic tourists than inland regions. This is consistent with Bujosa et al. (2015) and

Priego et al. (2015), who argued that coastal tourism is one of the main segments of Spanish domestic tourism.

We find that almost all the estimated parameters for the eleven monthly dummies, which were included to detect the fluctuation in seasonal patterns of Spain's domestic tourism demand, are positive and statistically significant at the 1% significance level. Thus, compared to January (base category), during the rest of the year, tourism demand is higher, especially in the summer months (July, August and September), due to an increase in leisure time coinciding with the periods of school vacations and public holidays.

The four annual dummies (2012 to 2014) included in the models intend to capture any omitted variables that vary over time but do not have cross-sectional variability and may be associated with changes in domestic tourism demand. In general terms, the results for these dummies illustrate a slight decrease in overnight stays in relation to 2011, perhaps reflecting a greater preference of Spanish residents for international destinations in recent years.

5.2. Climatic variables

a) Dispersion of temperature at the destination (Models 1 and 2).

If the rest of the variables are held constant, a 10 percent increase in the monthly temperature at the destination is associated with a 2.3 percent increase in overnight stays. In semi-elasticity terms, this means that an increase of 1° Celsius in the mean temperature at the destination causes a positive variation of 1.4% in the monthly domestic tourism inflows.

Model 2 shows that the number of overnights at the destination depends negatively on the temperature variability in this region (-0.803), measured by its standard deviation within the year. This is consistent with the fact that tourists dislike unexpected weather changes and prefer to travel to regions with less thermal amplitude

b) The temperature at both the destination and origin (Model 3).

Model 3 includes as separate variables the home and destination temperatures. Our findings show the importance of home temperature as a significant “push factor”. Negative elasticity (-0.425) and semi-elasticity (-0.026) values are estimated for the temperature at the origin. The results show that rainfall in region of origin *i* has a positive effect on tourist flows from region of origin *i* to destination region *j* (0.035). These effects could be explained by the fact that when home weather conditions are unfavourable, the probability of travelling to another region increases.

c) The effect of lagged variables (Model 4)

In most places, weather can change from minute to minute. Climate, however, is the average of weather over time and space. An easy way to differentiate them is that climate is what you expect, like a very hot summer, and weather is what you get, like a hot day with pop-up thunderstorms. Thus, if hotel bookings are made before current weather occurs, it is likely that the climate conditions of the preceding month may have a greater impact on destination choice than will the climate conditions of the month of travel. To assess that effect, Model 4 uses the one-month lag of climatic variables as predictors. The parameters of lagged values are somewhat higher, in absolute terms, than those in Model 3, for the temperature at both the destination (0.285) and origin (-0.438). The coefficients of the lagged rain variables are similar to Model 3.

d) The ratio of the temperatures between the destination and origin (Model 5).

Weather can be considered in relative terms. The relative temperature measures the weather comfort of a tourist's destination relative to that of the tourist's origin. Model 5 estimates the effect of relative weather to avoid the effect of $TEMP\_D_{jt}$ being independent of $TEMP\_O_{it}$ (Models 1 to 4). The results indicate that relative temperature (destination over origin) has a significant and positive effect on domestic tourist flows (0.360), while the effect of relative rainfall is negative (-0.037).

e) The effect of temperature varies with the seasons (Models 6 and 7).

The influence of weather on destination choice can change with the seasons. Models 6 and 7 allow to test whether the effect of weather differs depending on the season of the year. The estimation shows that the effect of temperature at the destination with respect to the reference category (autumn) is much higher in spring (0.898) and summer (0.300) than in winter (0.162). Additionally, as a push factor, the effect of the home temperature is more sensitive in the spring (-0.656) and summer (-0.487) seasons than in winter (0.119), when interpreting these coefficients from the reference category. In summer, 'sun and beach' tourism is influenced by climate. However, in winter and autumn, the temperature at the destination seems to have a lesser influence on destination choice.

Model 7 measures whether the effect of relative temperature varies with the seasons, and at the 10% level, the interaction with winter is not significant. However, the same conclusions noted above can be drawn for the rest of the seasons with respect to the reference category: spring (0.775) and summer (0.396).

f) The effect of temperature varies with the type of region (Model 8)

As we have seen in models 3 and 5, weather in the region of residence is a determinant of destination choice. However, it is also likely that tourists from regions with uncomfortable climates are more sensitive to weather at the destination. Model 8 predicts that the effect of temperature at the destination differs depending on climatic areas of origin, being less important for continental (-0.067) and Mediterranean regions (-0.182) compared to the oceanic regions (reference category). In other words, for residents in comfortable climate regions (Mediterranean), a better temperature at the destination has a lesser effect on destination choice than for residents in other regions.

Those differences might be an argument for tourists travelling outside of their region who are looking to experience a climate that differs from their home climate. Tourists are interested in experiencing something different; thus, climate difference between origins and destinations is probably a key motivation to travel (Lee & Crompton, 1992).

Table 3. Results for each alternative specifications of the gravity equation. Dependent variable: Ln (nights in *i* from origin *j*). Full sample.

	1	2	3	4	5	6	7	8
LnGDPpc	1.154***	1.123***	0.923***	0.906***	0.952***	0.922***	0.947***	1.048***
LnPOPULATION	0.966***	0.969***	0.996***	0.999***	0.992***	1.000***	0.996***	1.052***
LnDISTANCE	-0.542***	-0.579***	-0.499***	-0.508***	-0.504***	-0.492***	-0.504***	-0.559***
LnAREA	0.344***	0.442***	0.344***	0.340***	0.344***	0.343***	0.337***	0.350***
LnPARKS	0.351***	0.238***	0.349***	0.351***	0.353***	0.359***	0.365***	0.365***
D_CITY	0.357***	0.513***	0.366***	0.363***	0.369***	0.361***	0.355***	0.341***
D_COAST	0.855***	0.741***	0.833***	0.829***	0.809***	0.808***	0.798***	0.835***
D_EASTER	0.142***	0.145***	0.143***	0.129***	0.128***	0.131***	0.129***	0.118***
D_MADRID	2.357***	2.307***	2.346***	2.333***	2.352***	2.372***	2.371***	2.413***
LnTEMP_D	0.236***	0.174***	0.233***			0.117***		0.458***
LnTEMP_O			-0.425***			-0.418***		
LnRAIN_D	-0.060***	-0.061***	-0.060***					
LnRAIN_O			0.035***					
LnSDTEMP_D		-0.803***						
LnTEMP_D_L1				0.285***				
LnTEMP_O_L1				-0.438***				
LnRAIN_D_L1				-0.067***				
LnRAIN_O_L1				0.039***				
LnTEMP_R					0.360***		0.265***	
LnRAIN_R					-0.037***			
WINTER#c.LnTEMP_D						0.162***		
SPRING#c.LnTEMP_D						0.898***		
SUMMER#c.LnTEMP_D						0.300***		

WINTER#c.LnTEMP_O						0.119**		
SPRING#c.LnTEMP_O						-0.656***		
SUMMER#c.LnTEMP_O						-0.487***		
WINTER#c.LnTEMP_R							0.021	
SPRING#c.LnTEMP_R							0.775***	
SUMMER#c.LnTEMP_R							0.396***	
CONTINENTAL_O#c.LnTEMP_D								-0.067***
MEDITERRANEAN_O#c.LnTEMP_D								-0.182***
Constant	-18.590***	-17.400***	-16.170***	-16.020***	-16.860***	-16.690***	-16.790***	-19.230***
Seasonal dummy Feb	0.252***	0.250***	0.255***	0.253***	0.266***	0.266***	0.266***	0.248***
Seasonal dummy Mar	0.501***	0.520***	0.629***	0.566***	0.569***	0.0172	0.569***	0.715***
Seasonal dummy Apr	0.569***	0.600***	0.790***	0.761***	0.699***	0.801***	0.698***	0.940***
Seasonal dummy May	0.505***	0.547***	0.830***	0.794***	0.717***	0.831***	0.718***	1.052***
Seasonal dummy Jun	0.588***	0.642***	1.006***	0.950***	0.864***	1.679***	0.868***	1.296***
Seasonal dummy Jul	0.709***	0.768***	1.200***	1.151***	1.057***	2.586***	1.078***	1.563***
Seasonal dummy Aug	0.919***	0.980***	1.405***	1.346***	1.255***	2.785***	1.272***	1.760***
Seasonal dummy Sep	0.738***	0.793***	1.137***	1.120***	0.977***	2.435***	0.980***	1.413***
Seasonal dummy Oct	0.590***	0.635***	0.890***	0.923***	0.751***	1.513***	0.751***	1.095***
Seasonal dummy Nov	0.319***	0.343***	0.463***	0.539***	0.378***	1.044***	0.378***	0.557***
Seasonal dummy Dec	0.172***	0.175***	0.232***	0.292***	0.237***	0.818***	0.236***	0.268***
Year 2012	-0.052***	0.029*	-0.072***	-0.078***	-0.055***	-0.065***	-0.059***	-0.087***
Year 2013	-0.023	0.019	-0.068***	-0.057***	-0.061***	-0.076***	-0.068***	-0.099***
Year 2014	-0.024	-0.039**	-0.0323**	-0.025	-0.041**	-0.042***	-0.042**	-0.035**
Year 2015	-0.028*	0.025	-0.023	-0.022	-0.019	-0.021	-0.024	-0.036**
Observations	16,320	16,320	16,320	15,972	16,320	16,320	16,320	16,320
R-squared	0.781	0.784	0.786	0.788	0.786	0.787	0.787	0.792

Origin (O), destination (D) and the ratio of the weather condition of destination and origin (R)

Notes: Classic OLS estimation ***. p<0.01, ** p<0.05, * p<0.1

5.3. Estimation by season

To contrast the findings of our interactions with seasonal dummies, we split our sample into four subsamples focusing on the four seasons and re-estimate models 3 and 5. Every subsample includes the overnight stays registered in each season: winter (January, February and March), spring (April, May and June), summer (July, August and September) and autumn (October, November and December). The results are shown in Table 4.

As previously anticipated, Model 3´ shows that the weather at the destination is a strong determinant of domestic tourism, especially in spring and summer. In spring, the coefficients of the temperature (0.97) and rainfall (-1.18) at the destination are much higher than those in autumn (0.350/-0.24) and winter (0.49/-0.12).

Furthermore, the subsample analysis (Model 5´) confirms that the effect of relative temperature varies with the seasons. Relative weather (between home and destination) is an important motivation in the destination choice, especially in warm months.

Table 4. Results at sub-sample level.

	3´				5´			
	Winter	**Spring**	**Summer**	**Autumn**	**Winter**	**Spring**	**Summer**	**Autumn**
LnGDPpc	0.927***	0.755***	0.784***	1.087***	0.843***	0.766***	0.805***	1.069***
LnPOPULATION	1.007***	1.023***	1.023***	0.988***	1.014***	1.022***	1.027***	0.989***
LnDISTANCE	-0.540***	-0.547***	-0.551***	-0.511***	-0.491***	-0.540***	-0.546***	-0.500***
LnAREA	0.340***	0.324***	0.306***	0.323***	0.351***	0.319***	0.302***	0.324***
LnPARKS	0.336***	0.336***	0.380***	0.468***	0.325***	0.342***	0.383***	0.465***
D_CITY	0.624***	0.239***	0.068***	0.384***	0.641***	0.233***	0.068***	0.381***
D_COAST	0.558***	0.920***	1.305***		0.573***	0.914***	1.303***	0.417***
D_EASTER	0.117***	0.195***			0.117***	0.204***		
D_MADRID	2.327***	2.303***	2.272***	2.591***	2.321***	2.309***	2.268***	2.594***
LnTEMP_D	0.490***	0.971***	0.868***	0.350***				
LnRAIN_D	-0.124***	-1.184***	-1.087***	-0.244***				
LnTEMP_O	-0.230***	-0.041***	-0.006	-0.040***				
LnRAIN_O	0.084***	0.008	-0.010*	0.053***				
LnTEMP_R					0.386***	1.108***	0.945***	0.292***
LnRAIN_R					-0.095***	-0.020***	-0.004	-0.047***
Constant	-16.890***	-13.500***	-13.370***	-17.450***	-16.140***	-14.300***	-14.340***	-17.020***
Seasonal dummy Feb	0.260***				0.265***			
Seasonal dummy Mar	0.500***				0.573***			
Seasonal dummy May		0.081*				0.079*		
Seasonal dummy Jun		0.260***				0.228***		
Seasonal dummy Aug			0.201***				0.195***	
Seasonal dummy Sep			-0.088***				-0.096***	

Seasonal dummy Nov				-0.334***				-0.373***
Seasonal dummy Dec				-0.422***				-0.515***
Year 2012	-0.004	-0.089***	-0.084**	-0.098***	0.009	-0.061**	-0.098***	-0.099***
Year 2013	-0.041	-0.104***	-0.059*	-0.024	-0.067*	-0.069**	-0.081**	-0.034
Year 2014	-0.095***	-0.062**	-0.040	-0.003	-0.082**	-0.048*	-0.049	0.005
Year 2015	-0.052	-0.046	0.009	0.019	-0.071**	-0.016	-0.018	0.019
Observations	4,080	4,080	4,080	4,080	4,080	4,080	4,080	4,080
R-squared	0.795	0.81	0.775	0.829	0.792	0.809	0.777	0.829

Notes: Classic OLS estimation ***. p<0.01, ** p<0.05, * p<0.1

6. Discussion and Conclusions

This paper presents a review of the main approaches employed to study the effect of weather on tourist demand, as well as it illustrates the importance of considering the climatic variables of both the destination chosen by tourists and their place of residence. We used monthly flows of domestic tourists between different Spanish regions covering the period of 2011-2015.

One of our results indicates that higher temperatures in the destination than in the home region have a positive effect on overnight stays, and this same outcome can also be found in several other papers. In this regard, Bigano et al. (2005) estimated that the temperature at the destination is a significant pull factor in explaining the number of overnights by domestic tourists in Italy. Similarly, Taylor & Ortiz (2009) in the UK and Falk (2014) in Austria found the same result. In addition, our empirical result that shows that the temperature for the home regions is an important push factor coincides with the results reported in previous research on domestic tourism (Priego et al., 2015) and international tourism demand (Ridderstaat et al., 2014; Saverimuttu & Varua, 2014).

We also find that rainfall is an influential factor explaining domestic tourism demand, although its effect is opposite to the effect of temperature and of a much smaller magnitude. This result is less common in the literature, either because precipitation is not statistically significant (Taylor & Ortiz, 2009; Priego et al., 2015; Wilkins et al., 2018) or because an unexpected outcome is obtained (Bigano et al., 2005).

Furthermore, we verify the influence that past weather (lagged values of temperature and rain) can have on tourism demand. This result supports the important role that expectations about the weather play in tourists' decisions, in line with the findings of Bigano et al. (2005). Nevertheless, Taylor & Ortiz (2009) were not successful in testing this hypothesis, while Falk (2014) was only able to verify it for the overnight stays of foreign tourists.

Possibly, the most interesting results of this paper are those related to the simultaneous analysis of the impact of the pull and push climate factors on seasonal tourism demand and, more specifically, those associated with the effects of the differences between the destination and home climates, according to recent studies by Zhang and Kulendran (2016), Li et al. (2017), Li et al. (2018) and Turrión-Prats & Duro (2019). It is worth noting that not only was the relative temperature significant in our models but also, in most cases, the relative rainfall, something that has only been implicitly tested by Li et al. (2018), who used the "tourism climate index".

Interestingly, the estimated coefficients for these relative climatic variables (interpreted as elasticities) suggest that domestic overnight stays in Spain are strongly influenced by changes in the difference in temperature between tourists' origin and destination regions. Moreover, the magnitude of relative temperature elasticity represents 38% of the per capita income elasticity, and it even exceeds this value in estimates for the spring season.

Our results highlight that the marginal effects of the temperature and rainfall at the destination decrease with their levels at the origin. Our estimates also show that the weather pull factor has a lower incidence in destination choice when the tourist flows come from regions with a moderate or comfortable climate. On the other hand, tourists in regions with uncomfortable climates are more sensitive to weather at the destination. This may suggest that tourists seek experiences in a climate that differs from their home climate. Accordingly, the study of the relative climate, specifically between destination and origin, can facilitate customer segmentation by profiles that will permit members of the tourism industry to take specific actions depending on their customers' climatic areas of origin and weather preferences.

One of the main contributions of this study was testing whether the effect of climatic variables on tourist flows varies across different seasons. Our empirical results confirm that spring and summer tourism in Spain is more sensitive to weather conditions. During warmer seasons, the vast majority of hotel clients (apart from those in large cities) are beach users, and they prefer visiting places when the weather is continuously warm and sunny. In cold seasons, the temperature in the destination is a less important factor in tourists' destination choice, although snow precipitation is relevant for winter sports. This means that in autumn and winter, tourism planners must design activities that do not depend crucially on weather conditions, such as gastronomic tourism, business events, expositions or cultural and social activities.

We explored other modelling alternatives, such as the variability of the weather and lagged variables of temperature and rainfall. The inclusion of the standard deviations of these climatic variables enabled us to assess the effect of thermal oscillation on domestic tourism. Standard deviations of temperature and rainfall for each season were also considered to calculate the intra-annual effect of climatic variables on tourist flows and its variance.

On the other hand, the estimated parameters of lagged weather variables are higher than those corresponding to the travelling months (contemporaneous variables). As domestic trips are prepared in a shorter time frame than international trips, weather conditions of the preceding month may have a strong influence on destination choice. Therefore, it would be advisable for the industry to focus on analysing weather data when bookings are made, and the grounds for cancellation, to learn about the role of weather in destination choice.

One limitation of the present study is that we used only two factors of weather (temperature and rainfall) without considering a combined effect of the weather variables. Furthermore, the selection of a price variable to include in the model was particularly difficult. One alternative would be to construct an index expressing the cost of living of tourists in the different destinations relative to the cost of living in the origin.

We also believe that it would be interesting to extend this study by considering foreign overnight stays in Spain in order to compare the results with those reported here. Last, if there were available data, it would also be worthwhile to carry out a comparative analysis of the impact of climate on tourism demand that takes into account tourists' travel motivations (leisure and recreation, cultural, sports, …).

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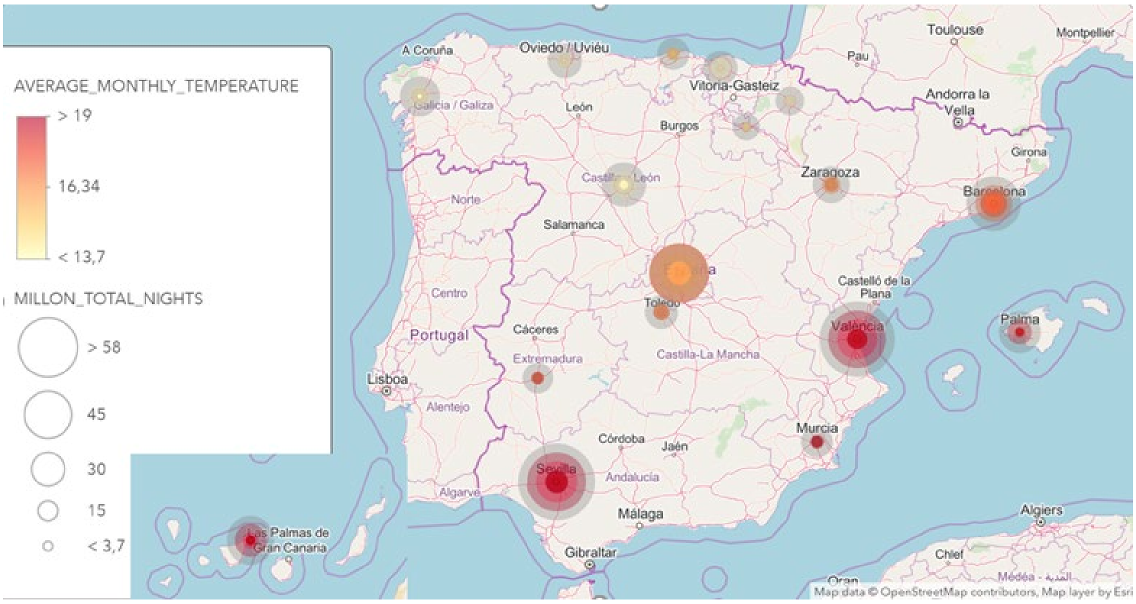
Annex I. Total annual overnights made by residents in other regions and average monthly temperature in the capital of destination region. Data: 2011-2015.



Source: Own elaboration from Spanish Statistical Office data. A map created using ArcGIS.

Annex II. Specifications of the models used.

MODEL	SPECIFICATIONS
Model 1: Standard modelling of climate at destination	$LnNIGHTS_{ijt} = \beta_0 + \beta_1 LnGDPpc_{it} + \beta_2 LnPOPULATION_{it} + \beta_3 DISTANCE_{ij} + \beta_4 LnAREA_j + \beta_5 PARKS_{jt} + \beta_6 D\_CITY_j + \beta_7 D\_COAST_j + \beta_8 D\_EASTER_t + \beta_9 D\_MADRID_j + \beta_{10} LnTEMP\_D_{jt} + \beta_{11} LnRAIN\_D_{jt} + \lambda_t + u_{ij}$
Model 2: Dispersion of temperatures	$LnNIGHTS_{ijt} = \beta_{12} + \beta_{13} LnGDPpc_{it} + \beta_{14} LnPOPULATION_{it} + \beta_{15} DISTANCE_{ij} + \beta_{16} LnAREA_j + \beta_{17} PARKS_{jt} + \beta_{18} D\_CITY_j + \beta_{19} D\_COAST_j + \beta_{20} D\_EASTER_t + \beta_{21} D\_MADRID_j + \beta_{22} LnTEMP\_D_{jt} + \beta_{23} LnRAIN\_D_{jt} + \beta_{24} LnSD\_TEMP\_D_{jt} + \lambda_t + u_{ij}$
Model 3: Both the climatic variables at destination and origin	$LnNIGHTS_{ijt} = \beta_{25} + \beta_{26} LnGDPpc_{it} + \beta_{27} LnPOPULATION_{it} + \beta_{28} DISTANCE_{ij} + \beta_{29} LnAREA_j + \beta_{30} PARKS_{jt} + \beta_{31} D\_CITY_j + \beta_{32} D\_COAST_j + \beta_{33} D\_EASTER_t + \beta_{34} D\_MADRID_j + \beta_{35} LnTEMP\_D_{jt} + \beta_{36} LnRAIN\_D_{jt} + \beta_{37} LnTEMP\_O_{it} + \beta_{38} LnRAIN\_O_{it} + \lambda_t + u_{ij}$
Model 4: Lag variable	$LnNIGHTS_{ijt} = \beta_{39} + \beta_{40} LnGDPpc_{it} + \beta_{41} LnPOPULATION_{it} + \beta_{42} DISTANCE_{ij} + \beta_{43} LnAREA_j + \beta_{44} PARKS_{jt} + \beta_{45} D\_CITY_j + \beta_{46} D\_COAST_j + \beta_{47} D\_EASTER_t + \beta_{48} D\_MADRID_j + \beta_{49} LnTEMP\_D_{jt-1} + \beta_{50} LnRAIN\_D_{jt-1} + \beta_{51} LnTEMP\_O_{it-1} + \beta_{52} LnRAIN\_O_{it-1} + \lambda_t + u_{ij}$
Model 5: The ratio of the climatic variables of destination and origin	$LnNIGHTS_{ijt} = \beta_{53} + \beta_{54} LnGDPpc_{it} + \beta_{55} LnPOPULATION_{it} + \beta_{56} DISTANCE_{ij} + \beta_{57} LnAREA_j + \beta_{58} PARKS_{jt} + \beta_{59} D\_CITY_j + \beta_{60} D\_COAST_j + \beta_{61} D\_EASTER_t + \beta_{62} D\_MADRID_j + \beta_{63} LnTEMP\_R_{ijt} + \beta_{64} LnRAIN\_R_{ijt} + \lambda_t + u_{ij}$
Model 6: Add to model 3 seasonal dummy	$LnNIGHTS_{ijt} = \beta_{65} + \beta_{66} LnGDPpc_{it} + \beta_{67} LnPOPULATION_{it} + \beta_{68} DISTANCE_{ij} + \beta_{69} LnAREA_j + \beta_{70} PARKS_{jt} + \beta_{71} D\_CITY_j + \beta_{72} D\_COAST_j + \beta_{73} D\_EASTER_t + \beta_{74} D\_MADRID_j + \beta_{75} LnTEMP\_D_{jt} + \beta_{76} WINTER\ x\ LnTEMP\_D_{jt} + \beta_{77} SPRING\ x\ LnTEMP\_D_{jt} + \beta_{78} SUMMER\ x\ LnTEMP\_D_{jt} + \beta_{79} WINTER\ x\ LnTEMP\_O_{it} + \beta_{80} SPRING\ x\ LnTEMP\_O_{it} + \beta_{81} SUMMER\ x\ LnTEMP\_O_{it} + \lambda_t + \lambda_t + u_{ij}$
Model 7: Add to model 5 seasonal dummy	$LnNIGHTS_{ijt} = \beta_{82} + \beta_{83} LnGDPpc_{it} + \beta_{84} LnPOPULATION_{it} + \beta_{85} DISTANCE_{ij} + \beta_{86} LnAREA_j + \beta_{87} PARKS_{jt} + \beta_{88} D\_CITY_j + \beta_{89} D\_COAST_j + \beta_{90} D\_EASTER_t + \beta_{91} D\_MADRID_j + \beta_{92} LnTEMP\_R_{ijt} + \beta_{93} WINTER\ x\ LnTEMP\_R_{ijt} + \beta_{94} SPRING\ x\ LnTEMP\_R_{ijt} + \beta_{95} SUMMER\ x\ LnTEMP\_R_{ijt} + \lambda_t + u_{ij}$
Model 8: Add to model 3 region of origin dummy.	$LnNIGHTS_{ijt} = \beta_{96} + \beta_{97} LnGDPpc_{it} + \beta_{98} LnPOPULATION_{it} + \beta_{99} DISTANCE_{ij} + \beta_{100} LnAREA_j + \beta_{101} PARKS_{jt} + \beta_{102} D\_CITY_j + \beta_{103} D\_COAST_j + \beta_{104} D\_EASTER_t + \beta_{105} D\_MADRID_j + \beta_{106} LnTEMP\_D_{jt} + \beta_{107} CONTINENTAL\_O\ x\ LnTEMP\_D_{jt} + \beta_{108} MEDITERANEAN\_O\ x\ LnTEMP\_D_{jt} + \beta_{109} LnRAIN\_O_{it} + \lambda_t + u_{ij}$

Source: Own elaboration